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Detection of River Boundary Edges from Remotely Sensed Image

Arshad Husain[1*], Shailendra Chaudhary[2]

[*1]*Research Scholar, GIS Cell, Motilal Nehru National Institute of Technology Allahabad, U. P.,India.*
[2]*Research Scholar, Department of Civil Engineering, Motilal Nehru National Institute of Technology Allahabad, U.P., India.*

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Abstract

Detection of river boundary from remotely sensed imagery plays avitalrole in space-based river studies. Procuring of river attributes such as length, width, branching pattern, boundaries and temporal variation are very useful in several applications such as surface water supply, transport, distribution, and dynamics. Typically, field surveying is commonly used method to study of these river characteristics.It is commonly time-consuming, labor intensive and expensive method to gather river attributes in the field. In particular, it is unsafe and not feasible to measure rivers in certain environments such as ice sheets, tidal flats, and floodplains.Therefore, satellite imageriesof the earth surface are playing critical roles in river studies.The detection of linear and curvilinear components is a classic subject in image processing studies. In present study a method for the detection of river boundary is described. Image of Linear Imaging and Self Scanning Sensor (LISS-III) of Resourcesat-2 satellite is used. Method includes three basic steps i.e. mosaicking of different tiles of images, edge detection and connected component analysis.

Keywords: *Boundary; Edge detection; Remote Sensing; River Satellite Image.*

1. INTRODUCTION

The measurement of river attributes including length, width, boundary, spatial and temporal deviations are typically performed by means of field work. It is a tedious, labor intensive and cost-oriented task to directly measure these attributes in the field. The evaluation of these attributes, can give valuable bits of information into various applications such as surface water supply, transport, dispersion, etc. It is also dangerous and difficult to quantify river attributes in specific conditions such as, ice sheets, salt marshes, and floodplains (Yang *et al.* 2013). In such circumstances, satellite imageries of the earth are facilitating the solution to overcome these hurdles in river attribute measurement. Nowadays, optical remotely sensed imageries play significant role in river studies (river's attribute calculation). Detection and generation of rivers and their mask from remotely sensed imagery is a critical task. From the generated mask of river, width can be directly measured (Pavelsky *et al.* 2008), and subsequently certain additional key information i.e. river depth, flow velocity, and discharge can be further determined. Rivers are open water bodies; they appear as dark, continuous, and curvilinear features in the satellite imagery due to very low visible/near-infrared spectral reflectance. Formation of river networks is primarily organized by surface topography, due to this determination of river features has received a huge attention. Subsequently Digital Terrain Models (DTMs) have become the primary data source to determine drainage networks using different method such as contributing area methods, area-slope methods, and grid network ordering methods (Liu *et al.* 2014). Only a few research articles have mentioned the limitation of DTMs-derived drainage networks and tried to detect rivers from optical and Synthetic Aperture Radar (SAR) images (Benstead and Leigh, 2012). Three primary detection approaches namely manual interpretation (Trigg *et al.* 2012), semi-automatic (Dillabaugh *et al.* 2002) and ancillary-data-support (Pai and Saraswat, 2013; Lau and Franklin, 2013) are used in these studies. Anovel automated method is proposed to detect rivers using high-resolution SAR images (Klemenjak *et al.* 2012). Proposed method includes adaptively created training sampling and supervised image classification. Concept of Support Vector Machine (SVM) classifier and supervised image classification are used to delineate

***Arshad Husain**
email: rgi1501@ mnnit.ac.in

rivers (Güneralp *et al.* 2013). The proposed automatic method shows good completeness for delineating wide rivers while, less attention is applied to identify the thin present rivers in images. These thin rivers present in images have very lower spectral contrast as compared to the background of image. A multi-scale classification approach to detect the thin river rivers is proposed (Jiang *et al.* 2014). The proposed method noticed the limitations of studying rivers at mono-scale. However, the spectral contrast along thin river sequences is typically unbalanced due to differences in river depth, sediment loads etc. In order to detect the rivers and their attributes it is necessary to know the characteristics of rivers in remotely sensed imagery. The key and probable characteristics of rivers in optical visible/near-infrared remotely sensed imagery are, rivers appear as curvilinear features instead of blob-like features, rivers exhibit Gaussian-shaped cross-sections, and rivers are continuous and not a series of disconnected curvilinear segments.

In this study a semi-automated approach to detect the boundary edges of rivers in remotely sensed imagery is proposed. The used satellite imaginary is geo-referenced therefore; detected boundary edges can be further utilized to calculate the length and width of the river.

2. TEST DATA

Study area of present study is Triveni Sanagm region of Allahabad city, Uttar Pradesh, India (25°20'19.7"N, 81°58'43.8"E).The satellite imaginary used in present study is taken from the Bhuvan official website(http://bhuvan.nrsc.gov.in/data/download/index.php). The data is obtained from Linear Imaging and Self Scanning Sensor (LISS-III) of Resources at -2 which operates in three spectral bands in Visible and Near-Infrared (VNIR) and one band in Short wave Infrared (SWIR) with 24 meter spatial resolution and a swath of 141 km. Two tiles (Fig. 2 and Fig. 3) are used in order to cover the whole study area. The specification of tiles is shown in Table1.

Fig. 1: Google Earth image of test site

Table 1. Specification about Dataset

Spec.	Tile 1		Tile 2	
Name	G44P15		G44Q03	
Coverage	Upper left	X = 81.75E, Y = 25.5N	Upper left	X = 82E, Y = 25.5N
	Upper right	X = 82E, Y = 25.5N	Upper right	X = 82.25E, Y = 25.5N
	Lower right	X = 82E, Y = 25.25N	Lower right	X = 82.25E, Y = 25.25N
	Lower left	X = 81.75E, Y = 25.25N	Lower left	X = 82E, Y =25.25N
Date Of Pass	24-oct-08		24-oct-08	
File Format	Geotiff		Geotiff	
Spatial Resolution	0.000225 Degree/24 meter		0.000225 Degree/24 meter	

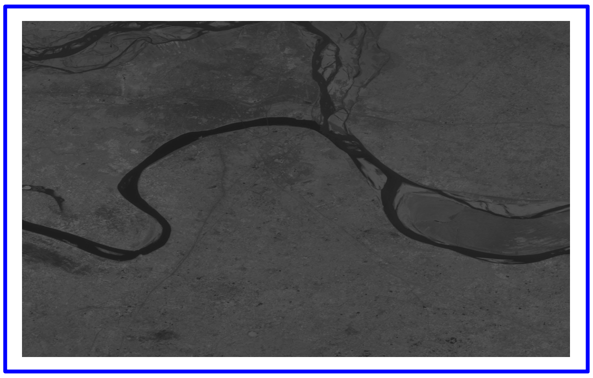

Fig. 2: Perspective view of first tile (G44P15) image

Fig.3:Perspective view of second tile (G44Q03) image

3. METHOD

Three basic steps are incorporated to detect the boundary edges of river; initially the mosaicking of tiles is performed, after that canny edge detection technique is performed at mosaicked image. In last step an area based connected component analysis is performed. Fig.4 shows the detailed process outline of the method. All the step of method is described in detail in the following section.

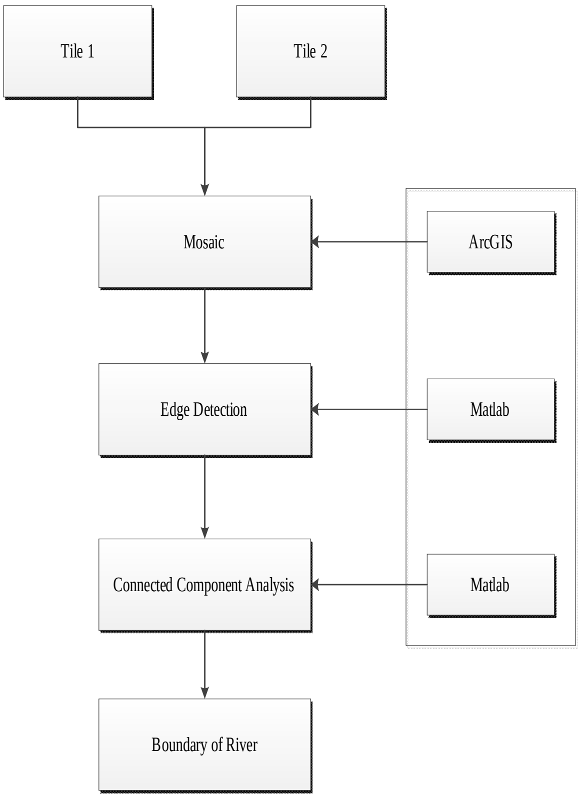

Fig. 4: Flowchart outline of the proposed method

3.1 Mosaicking of Tiles

Mosaicking of raster dataset is used in such cases at in which two or more adjacent raster datasets need to be merged into one entity. In present study both tiles are mosaicked with each other using the ArcGIS 10.3.

In order to perform the mosaicking, first of all an empty raster is created with the help of Data Management tools of Arc Toolbox. In particular of Data management tools Raster option is selected and an empty raster is created. Further, both the tiles are added in ArcMap with add data option and Mosaic option is selected from Raster Dataset of Arc Toolbox. Both the tiles are provided as input in Input Rasters option and earlier created empty raster is provided as target raster option. Fig. 5 shows the final mosaicked image of both tiles.

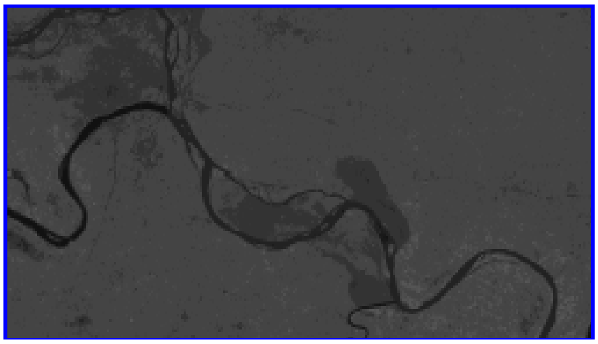

Fig. 5: Perspective view of mosaicked image

3.2 Edge Detection

After performing mosaicking, mosaicked image is used for the detection of edges. Canny edge detection method has been chosen to detect the edges in mosaicked image (Canny, 1986). The Canny edge detection includes noise reduction using Gaussian filtering, computing the depth gradient and finding the maximum localized edges, and finally tracing the detected edges to include the weaker gradients if they exhibit natural extension to the strong edges. It finds a lot of edges in mosaicked image besides the boundary edges of rive (Fig.6). These boundary edges exist on the sides of the river which exhibits the highest point density across the whole scene. Canny edge detection technique includes all the thin and thick edges of mosaicked image.

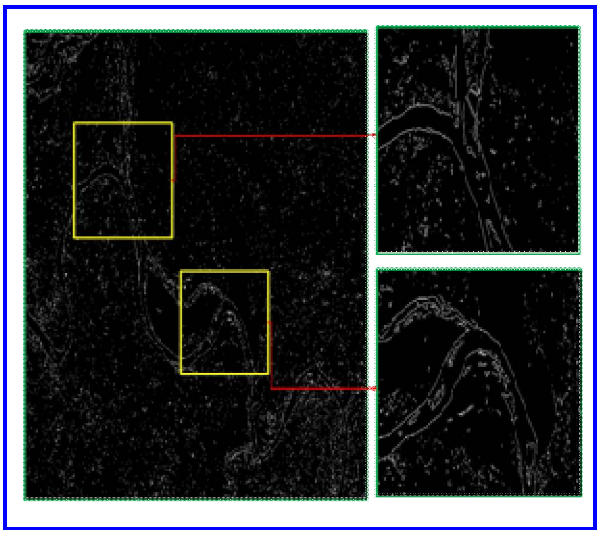

Fig. 6: Detected edges of mosaicked image

3.3 Connected Component Analysis

An area based connected component analysis is performed at detected edges. In order to perform the connected component analysis, an edge filtering process is used in which edges having less than a particular number of connected neighbourhood (*no_nhs*) are filtered out and remaining connected edges (having greater or equal to the threshold number of connected neighbourhood) are labelled with unique integer number.

Further, an area based constraint is applied at each label that area of each label (*L_Ar*) should be greater than a particular threshold. After applying this constraint, all the edges except the longest connected edge are filtered out from the image.

4. RESULT & DISCUSSION

Two different parameters are used in last step of the method. The used values of these parameters are shown in Table 2.

Table 2. Parameters and their used values in various steps of proposed method

Steps	Parameters	Used Value
Connected component analysis	number of connected neighbourhood (*L_Ar*)	8
Connected component analysis	area of each label (*L_Ar*)	0.009216km^2

The available option for number of connected neighbors is four, eight, twenty-four and so on. In order to remove smaller edges eight numbers of connected neighbors are chosen. In case of twenty four numbers of connected neighbors, some portion of boundary edge of the river is filtered out. If four numbers of connected neighbors are chosen, in such case many small edges which are not area of interest are remained. The total area covered in this study is 2404 kilometer^2(km^2), and the spatial resolution of the image is 24 meter, so in case of eight connected neighbors total connected area will be 0.005184 km^2. So, the area of each label should be greater than the area of eight connected neighbors and must be less than the area of twenty four neighbors which is 0.1444 km^2. Fig. 7 represents the detected boundary line after applying all the steps of the pipeline.

Mosaicking of the tiles is required manual processing in ArcGIS. Remaining steps of the method is coded and performed using Matlab2013a installed in standard PC (OS: Windows7: 64bit, CPU: Intel Core i3@2.4GHz, RAM: 3GB). Execution time of the proposed method is 19.92seconds;time tagged in mosaicking is excluded because it takes manual processing.

5. CONCLUSION & FUTURE RECOMMENDATION

In present study a method for river boundary detection is explained, and method is tested at LISS-III satellite imaginary of Triveni Sangam region of Allahabad city, Uttar Prasesh, India. Results are generated on the optimized values of parameters listed in Table 2.Two different softwares i.e ArcGIS 10.3 and Matlab2013a is used for processing the detailed method. The boundary edges of river are detected. Future work will be focused on developing such methodologies to automatically determine the optimized value of employed parameters.

Fig. 7: Detected boundary edges of river

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